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Radio Frequency Interference Detection for Passive Remote Sensing Using Eigenvalue Analysis

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Acronym List

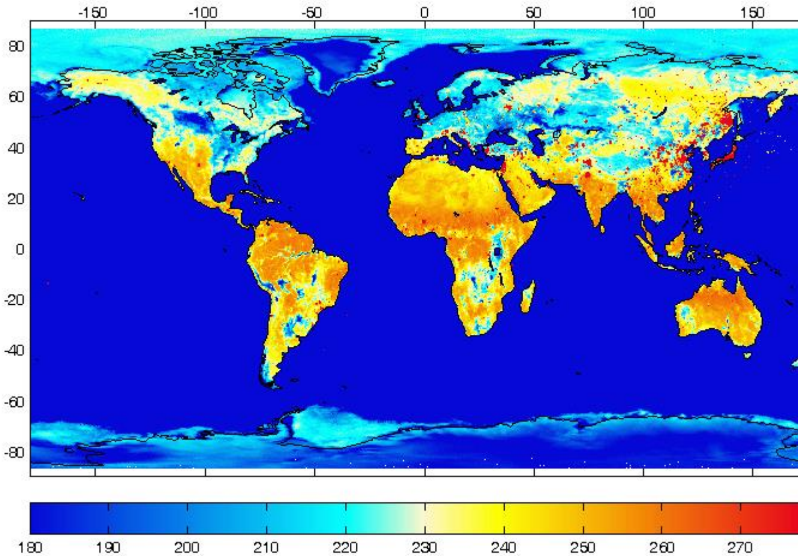
Acronym	Definition
ABS()	Absolute Value
AS&D	ASRC Federal Space and Defense
AUC	Area Under Curve
CERBM	Complex Entropy Rate Bound Minimization
CONUS	Continental United States
CQAMSYM	Complex Quadrature Amplitude Modulation
CSK	Complex Signal Kurtosis
CW	Continuous Wave
dB	Decibel
DDC	Digital Down Converter
DSP	Digital Signal Processing
DVB-S2	Digital Video Broadcasting - Satellite - Second Generation
ERBM	Entropy Rate Bound Minimization
ESTO	Earth Science Technology Office
FB	Full Band
FPGA	Field Programmable Gate Array
Gbps	Billions of Bits per Second
GMI	GPM Microwave Imager
GPM	Global Precipitation Measurement
GSFC	Goddard Space Flight Center

Acronym	Definition
H	Horrizontal
ICA	Independent Component Analysis
INR	Interference to Noise Ratio
MME	Maximum Minimum Eigenvalue ratio
MSE	Mean Square Error
NASA	National Aeronautics and Space Administration
NCCFASTICA	Non Circular Complex Fast ICA
PI	Principal Investigator
QPSK	Quadrature Phase Shift Keying)
RADAR	RAdio Detection And Ranging
RF	Radio Frequency
RFI	Radio Frequency Interference
ROACH	Reconfigurable Open Architecture Computing Hardware
ROC	Receiver Operating Characteristic
RRCOS	Root Raise Cosine
RSK	Real Signal Kurtosis
SB	Sub Band
SERDES	Serializer / Deserializer
SMAP	Soil Moisture Active Passive
V	Vertical

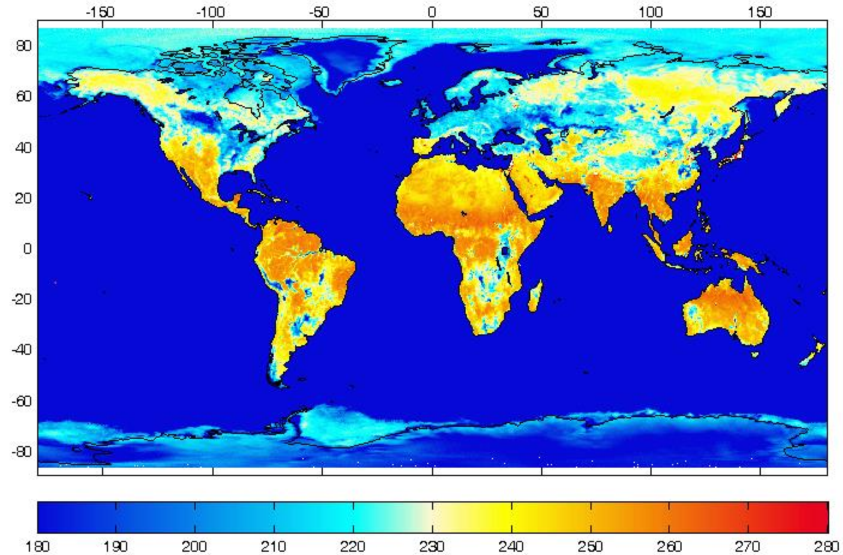
Motivation

- Unmitigated RFI (Radio Frequency Interference) can cause errors in science measurements
  - L- and C-Band: soil moisture measurements over land
  - L-, C- and X-band: ocean salinity, sea surface temperature, wind speed direction
  - K band: water vapor, liquid water
- Approach
  - RF front end development for 18 GHz (K band)
    - These allocations are known to be corrupted by direct broadcast services
  - Digital back end to allow sophisticated RFI detection and mitigation techniques

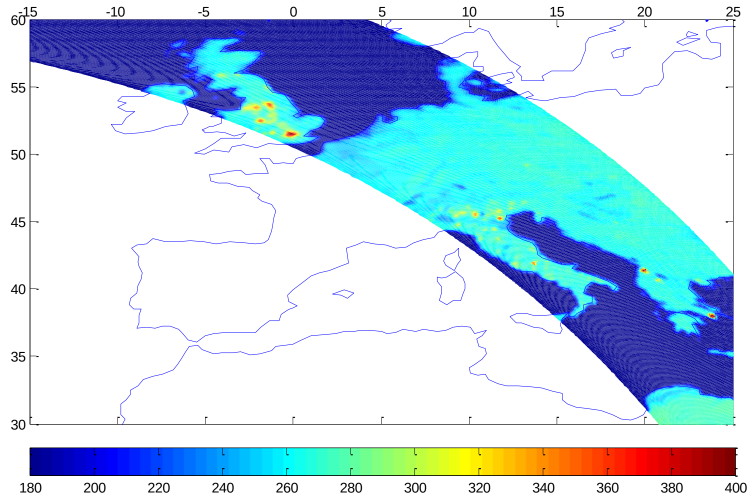
L, X band RFI



SMAP TA H-pol
1400 MHz



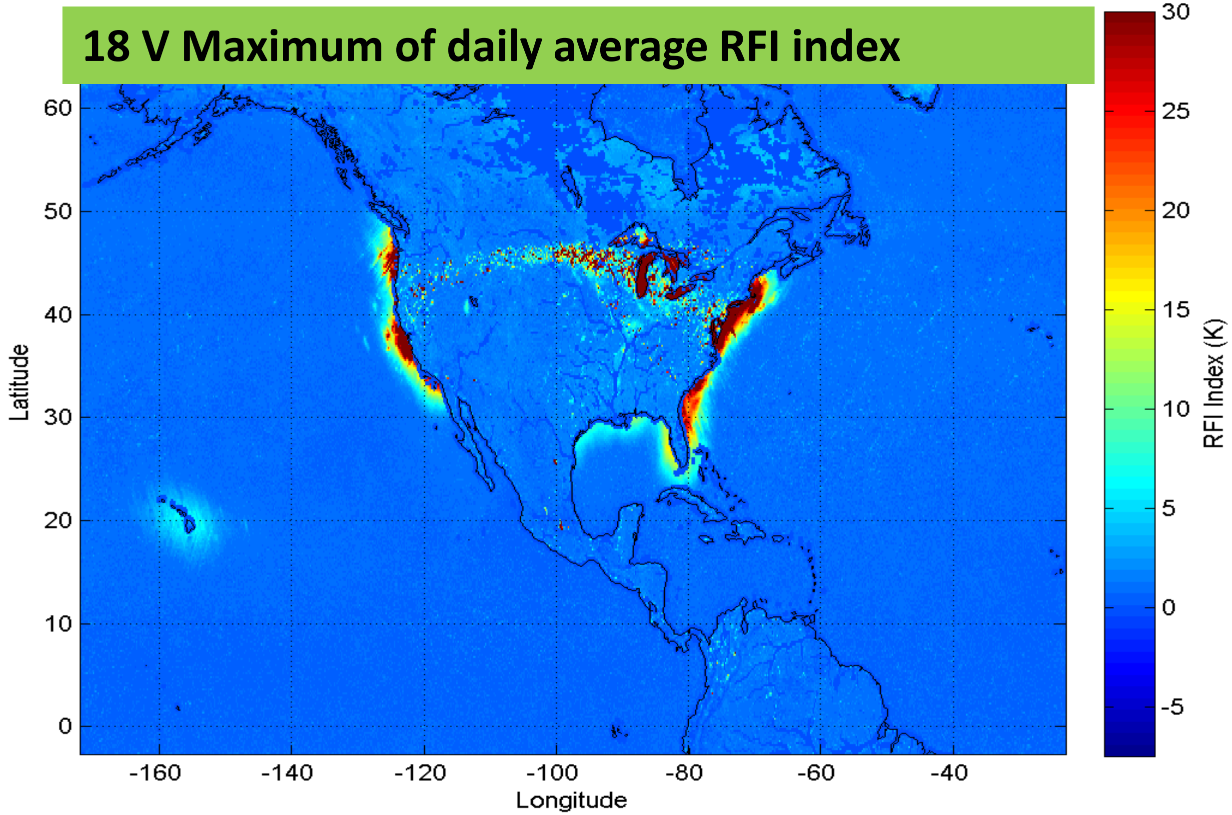
SMAP TA H-pol filtered



10 GHz GMI
Tb V-pol
(Vertical)

SMAP (Soil Moisture Active Passive) algorithms developed previously under ESTO (Earth Science Technology Office)

RFI from Geosynchronous Satellites Reflecting from the Surface



GMI data

Picture from David W. Draper, [1]

The 18 GHz Channel sees significant RFI from surface reflections around CONUS (Continental United States) and Hawaii

Real Signal Kurtosis (RSK)

Given a complex baseband signal $z(n) = I(n) + jQ(n)$, the fourth standardized moment is computed independently for both the real and imaginary vectors, I and Q, as was used in SMAP[3].

$$\mathrm{RSK_I} = \frac{\mathbb{E}[(\mathrm{I} - \mathbb{E}[\mathrm{I}])^4]}{(\mathbb{E}[(\mathrm{I} - \mathbb{E}[\mathrm{I}])])^2} - 3 \quad , \qquad \mathrm{RSK_Q} = \frac{\mathbb{E}[(\mathrm{Q} - \mathbb{E}[\mathrm{Q}])^4]}{(\mathbb{E}[(\mathrm{Q} - \mathbb{E}[\mathrm{Q}])])^2} - 3$$

The test statistic, RSK [2,3] (Real Signal Kurtosis), is then defined as

$$\mathrm{RSK} = \frac{|\mathrm{RSK_I}| + |RSK_Q|}{2}$$

Complex Signal Kurtosis

Complex signal kurtosis (CSK) [4,5] is used to improve ability of the digital radiometer to detect RFI. It makes use of additional information in complex signals.

Given a complex baseband signal $z(n) = I(n) + jQ(n)$, *moments* $\alpha_{\ell,m}$ of $z(n)$ are defined as

$$\alpha_{\ell,m} = \mathbb{E}\left[(z - \mathbb{E}[z])^{\ell}(z - \mathbb{E}[z])^{*m}\right], \ell\ , m \ \in \mathbb{R} \geq 0$$

With $\sigma^2 = \alpha_{1,1}$, *Standardized moments* $\varrho_{\ell,m}$ can then be found as

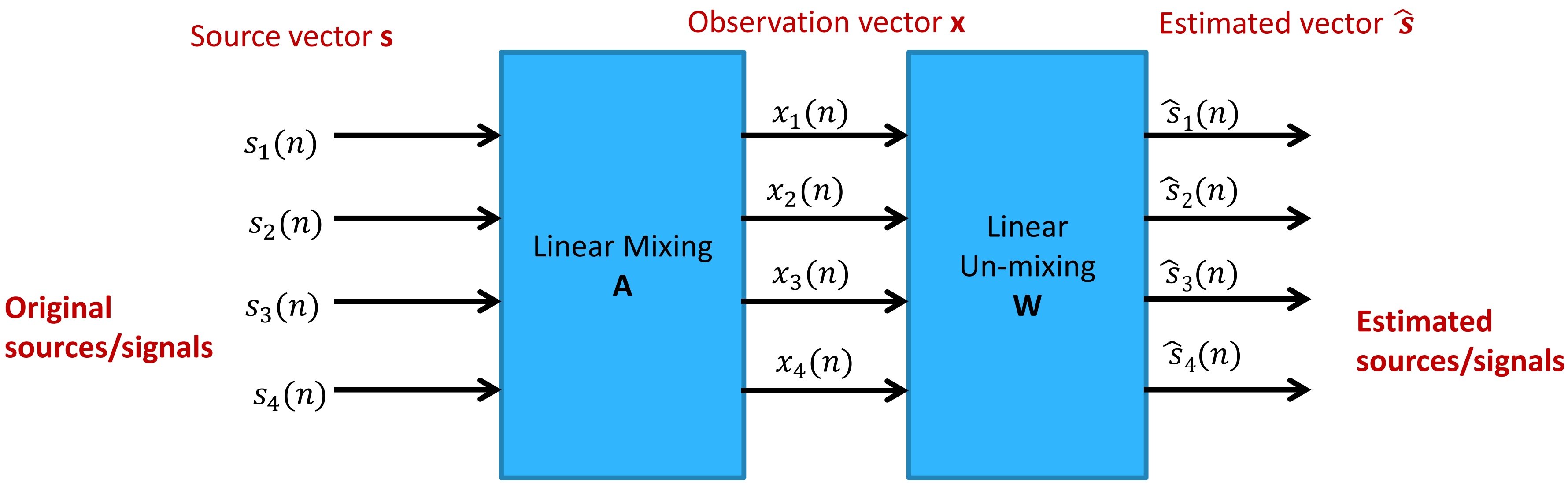
$$\varrho_{\ell,m} = \frac{\alpha_{\ell,m}}{\sigma^{\ell+m}}$$

Leading to the CSK (Complex Signal Kurtosis) RFI test statistic used [4].

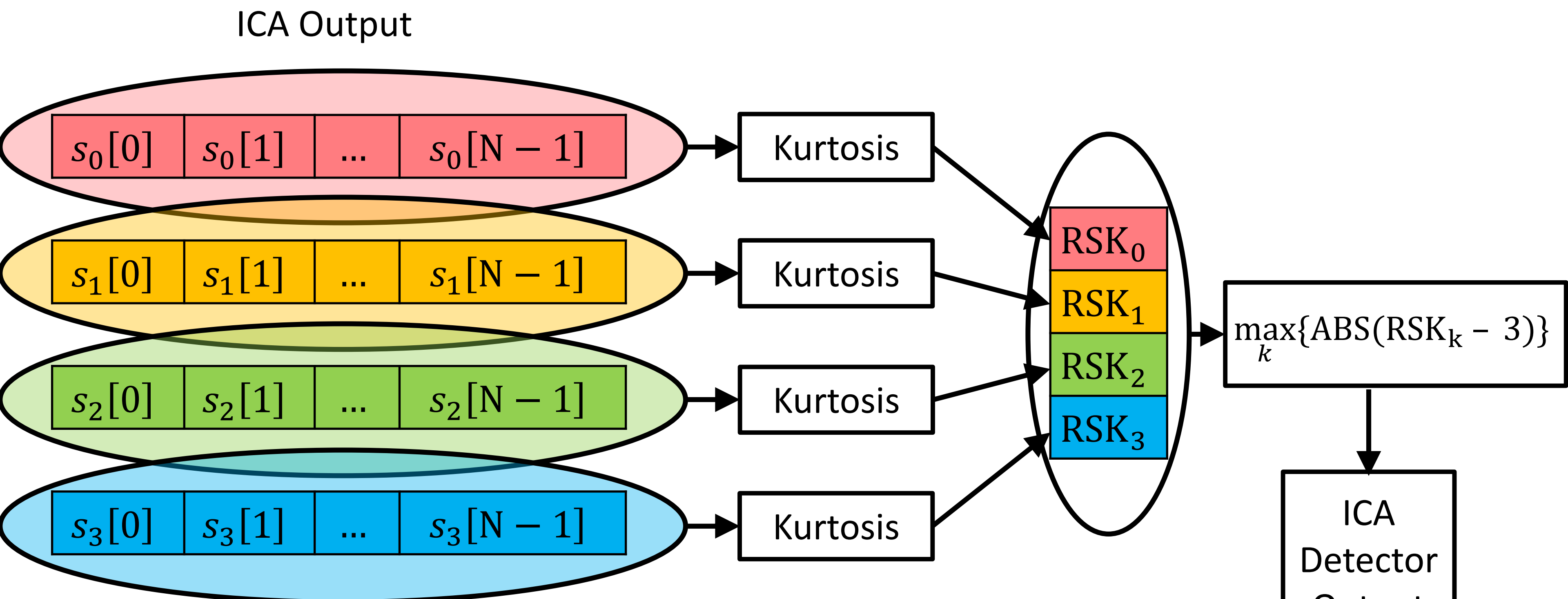
$$C_K = \frac{\varrho_{2;2} - 2 - \left|\varrho_{2;0}\right|^2}{1 + \frac{1}{2}\left|\varrho_{2;0}\right|^2}$$

Independent Component Analysis

- ICA [6] uses higher order statistics to perform blind source separation
- This suggests it may be useful for separating RFI from Gaussian noise in the radiometry context, studied in [7].
- We assume noise and RFI are statistically independent sources, mixing is linear, sources are non Gaussian
- Mixture model: **x = As**, observe **x**
- $\hat{\boldsymbol{s}}$ = **Wx**, $\hat{\boldsymbol{s}}$ is the estimated independent source



ICA RFI Detection



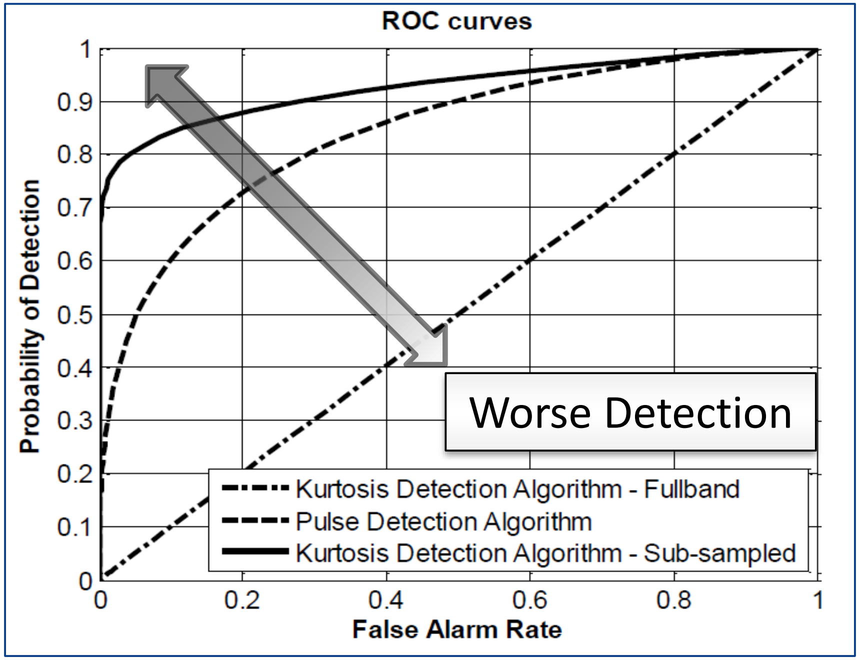
Step 1: Take Kurtosis of each estimated independent component vector

Step 2: Select the kurtosis value that deviated the furthest from 3

ROC Curves and AUC

- Each point on an ROC curve can be represented by the set {FAR, PD}
  - {False alarm Rate , Probability of Detection}
- ROC curves will generate from (0,0) to (1,1) by varying the threshold
- Poor detectors are close to the 1:1 line
- Better detectors show higher PD and smaller FAR
- **Figure of Merit = Area Under Curve (AUC)**
  - 0.5≤AUC ≤1
  - When AUC = 0.5 detector does not work
  - When AUC = 1 the detector works perfectly

Better Detection



Worse Detection

ROC curve example, from [8].

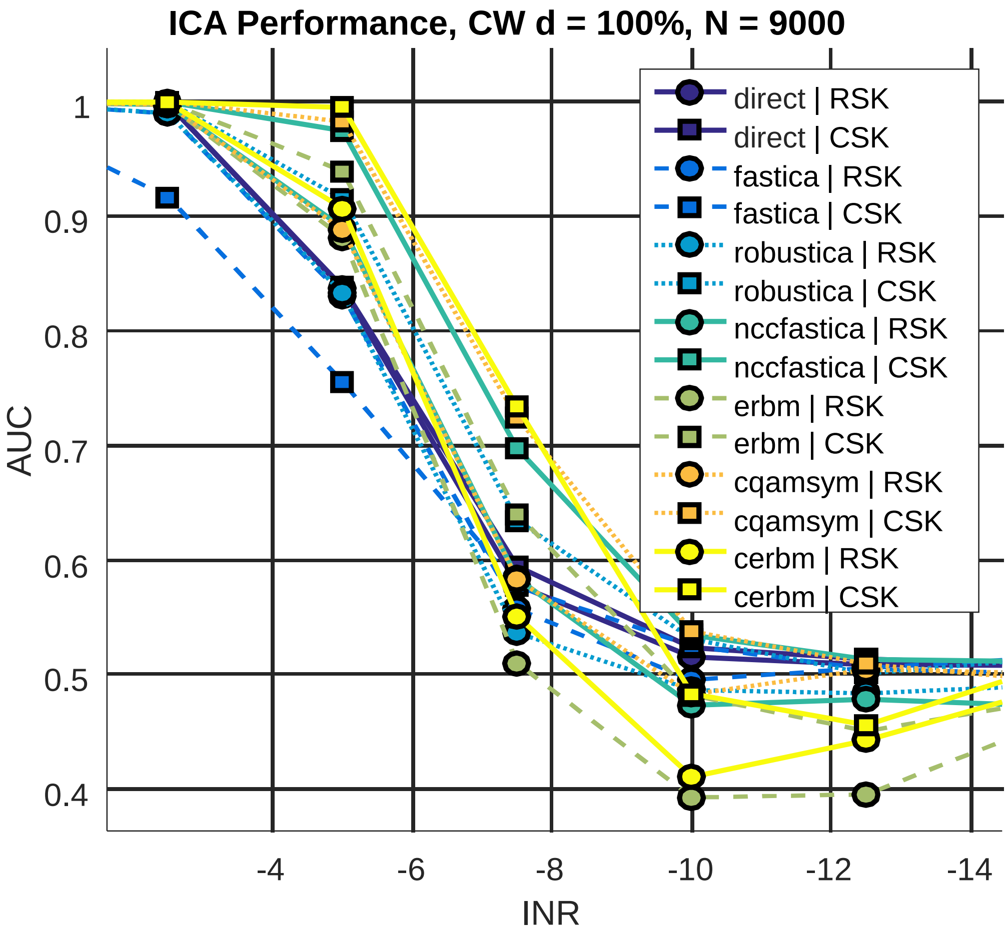
AUC = 1

AUC = 0.5

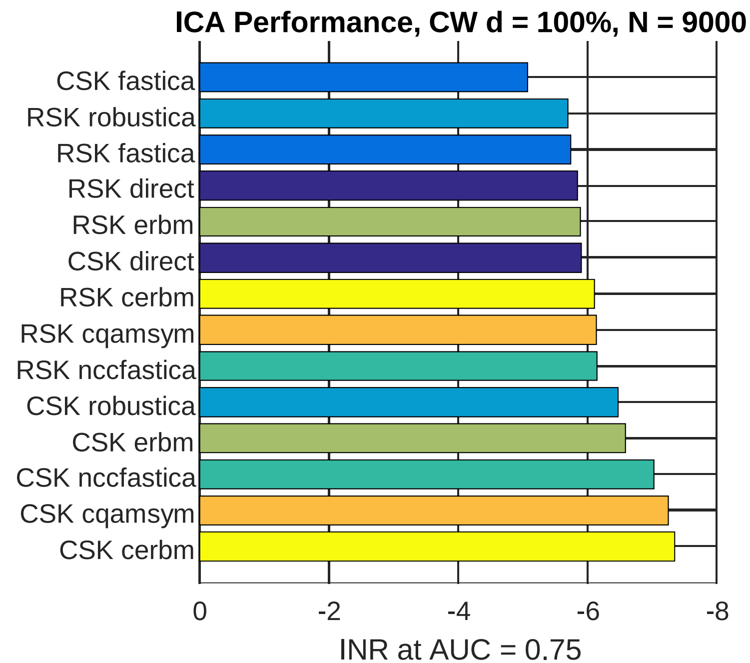
Better Detection

Worse Detection

AUC Results- ICA Performance - CW



More ICA results in [7], generally a marginal improvement in detection is seen



Various ICA algorithms are tested [9,10,11,12,13,14,15,16,17].
No ICA pre-processing is done on 'direct' data sets.

RSK = Real Signal Kurtosis
CSK = Complex Signal Kurtosis

Eigenvalue Approach

- Two objectives:
  - Detection: Identify power measurements that have been contaminated with interference
    - The Minimum Maximum Eigenvalue (MME) approach, adapted from the cognitive radio context [10], is applied here for RFI detection in passive remote sensing.
  - Excision: Accurately guess what the power measurement would have been if the interfere were not there

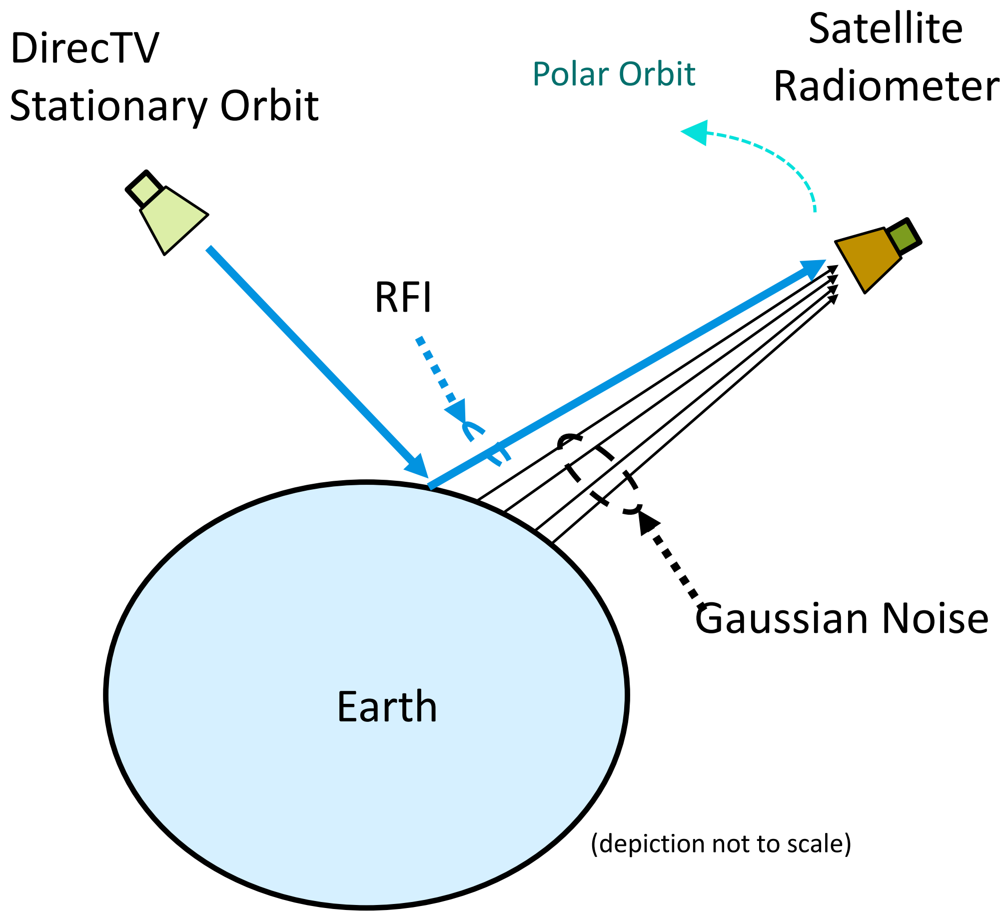
Conceptual Signal Model

Hypothesis Test / Signal Model

$$\mathcal{H}_0: x[k] = w[k]$$
$$\mathcal{H}_1: x[n] = w[k] + r[k]$$

$$SNR = \frac{P_s}{\sigma_w^2} \qquad \mathrm{P_s} = \mathrm{E}[(r[k])^2]$$

$w[k] \sim \mathcal{N}(0, \sigma_w^2)$ = Thermal Noise
$r[k]$ = RFI



Measure the Sample Covariance (Oversampled)

Given our sampled signal x,

$$x_i(n) \equiv x[nM + i - 1] \quad i = 1,2, \dots , M$$

$$\mathbf{x}(n) \equiv [x_1(n), x_2(n), \dots x_M(n)]^T$$

$$\hat{\mathbf{x}}(n) \equiv [\mathbf{x}^T(n), \mathbf{x}^T(n-1), \dots \mathbf{x}^T(n-L+1)]^T$$

$$\mathbf{R}_x = \mathbb{E}[\hat{\mathbf{x}}(n)\hat{\mathbf{x}}^H(n)]$$

$$\mathbf{R}_x(N_s) \equiv \frac{1}{N_s} \sum_{n=L-1}^{L-2+N_s} \hat{\mathbf{x}}(n)\hat{\mathbf{x}}^H(n)$$

The Eigenvalues of the covariance matrix are found

$$\lambda_1 > \lambda_2 > \cdots > \lambda_{ML}$$

The test statistic is then formed as

$$\mathbf{T}_\lambda = \frac{\lambda_{max}}{\lambda_{min}}$$

Eigenvalue Noise Power Estimate

Scale the minimum eigenvalue of the covariance matrix to estimate the variance of the Gaussian thermal noise. The limiting distributions from [19] help derive the scaling factor.

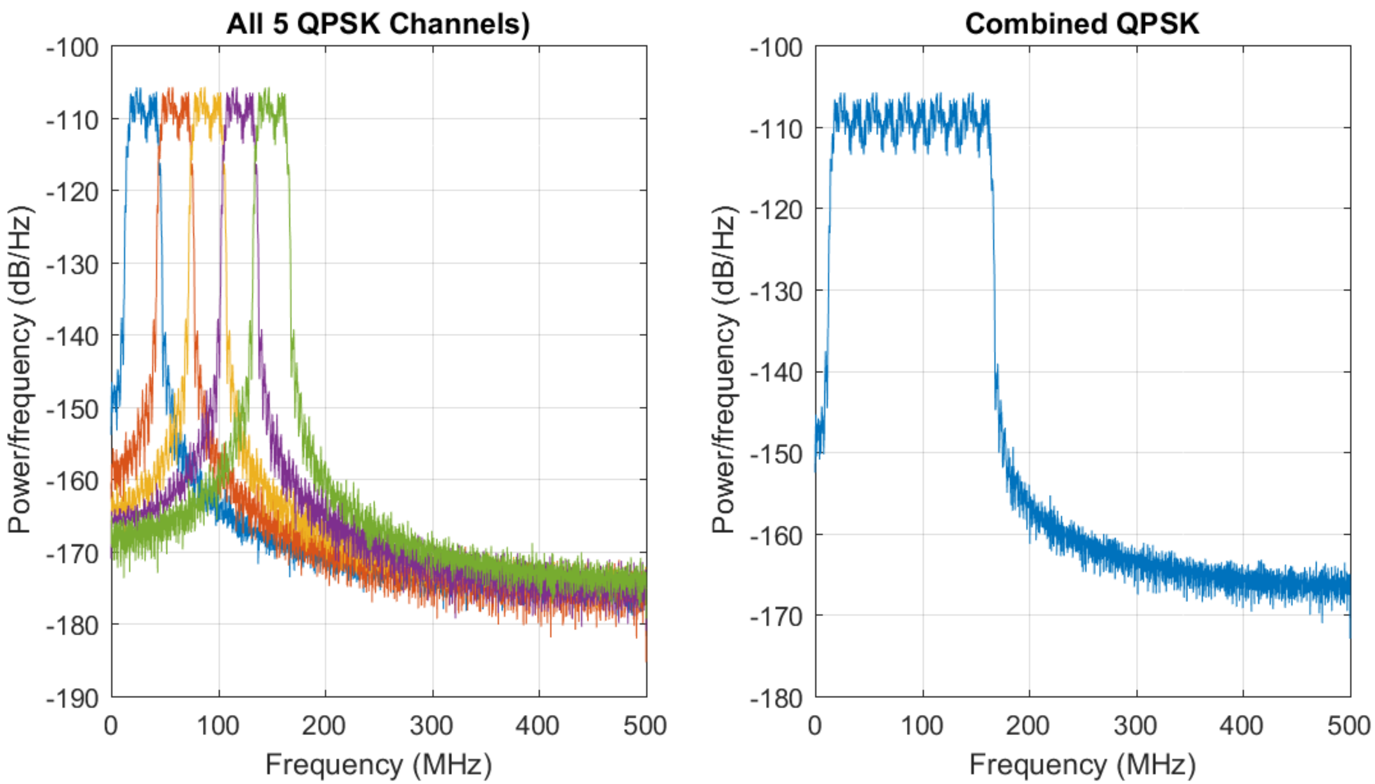
$$\mathbf{R}_x \rightarrow \lambda_1 > \lambda_2 > \ \dots \geq \lambda_{ML}$$

$$\lim_{N_s \rightarrow \infty} \lambda_{min} = \sigma^2 (1 - \sqrt{y})^2$$

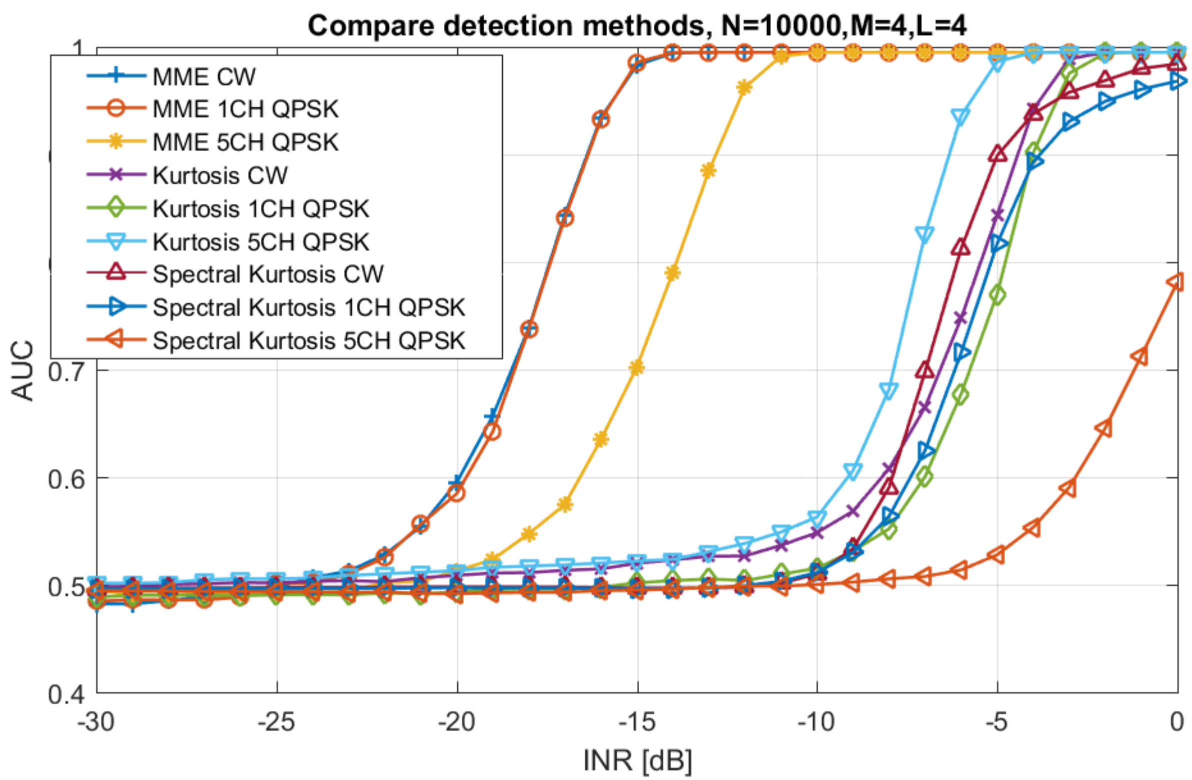
$$\lim_{N_s \rightarrow \infty} \lambda_{max} = \sigma^2 (1 + \sqrt{y})^2$$

$$\widehat{\sigma_{\mathrm{w}}^2} = \lambda_{min} \frac{N_s}{\left(\sqrt{N_s} - \sqrt{ML}\right)}$$

Wideband RFI – 5 QPSK Channels



MME Detection Results



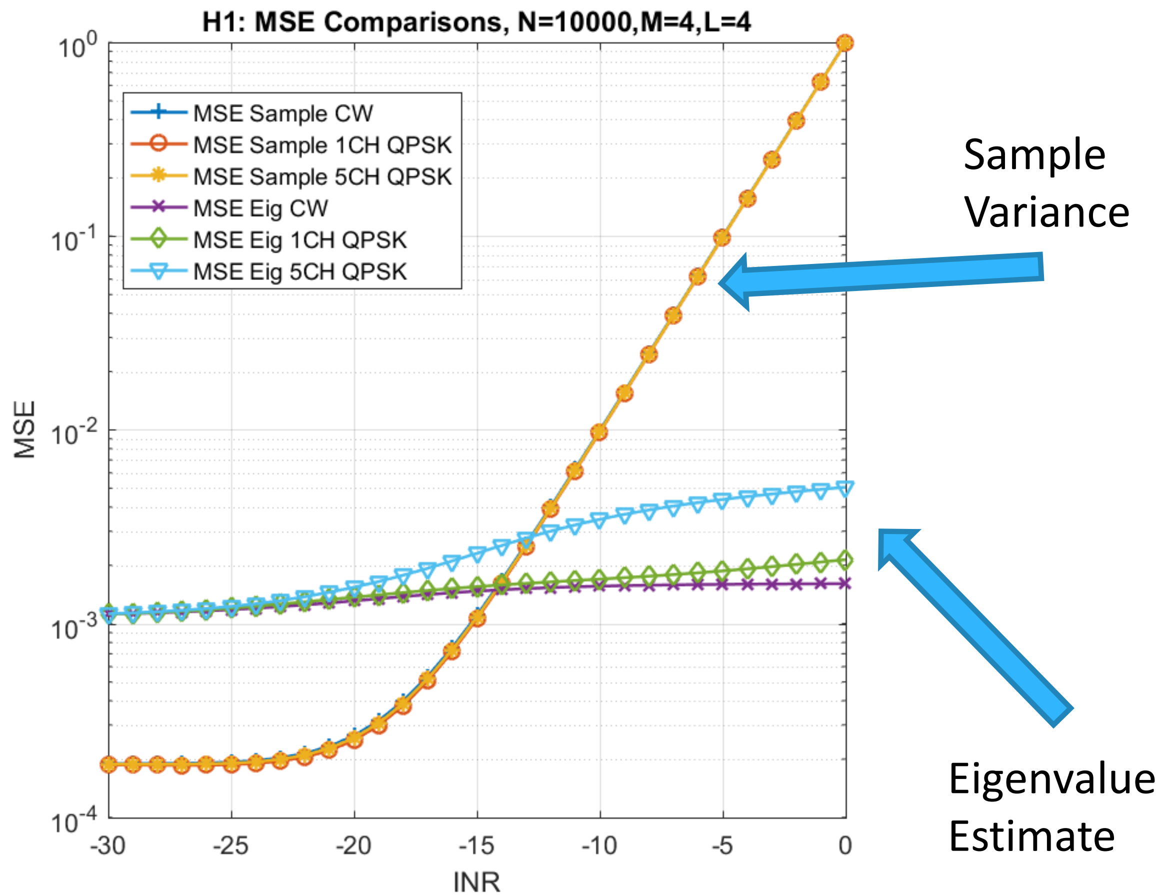
Eigenvalue Detection method greatly outperforms all other methods tested (Kurtosis[2,3] and Spectral Kurtosis[20])

RFI Excision Performance

Sample Variance
Compared to
Eigenvalue Variance Estimate

Eigenvalue Variance Estimate outperforms sample variance at interference levels of -14db INR and greater.

Eigenvalue variance estimate accuracy depends on the complexity of the RFI



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